

Technological innovations

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Take away: 4 new opportunities

- ❑ Continuous, rich recording from a variety of sensors
- ❑ Algorithms to process data to reduce coding time
- ❑ *Context-sensitive* data collection to collect data and prompt for self-report at desired times and places
- ❑ *Context-sensitive*, personalized interventions

Your task...

What are the possibilities for *your* research?

Relevance to health research (1)

- ❑ Ability to better study how context (people, places, things) impacts behavior

- ❑ Examples
 - Measurement of moderate intensity or greater physical activity
 - Dietary decision making
 - Making every interruption count

Relevance to health research (2)

- ❑ Ability to create and measure impact of “just-in-time” interventions

- ❑ Example: physical activity
 - Measurement is important, but we already know people don’t get enough physical activity!
 - Just-in-time detection of activity for positive reinforcement

Overview

- ❑ New developments
- ❑ Examples
 - Context-sensitive experience sampling
 - Portable kit of “tape on” environmental sensors
 - PlaceLab
- ❑ Emerging opportunities
- ❑ Challenges

New developments

- **New developments**
- Examples
- Emerging opportunities
- Challenges

Data collection in the (not-so-distant) future

- ❑ Record and save everything from subjects:
 - 24/7 video stream (160x120 resolution, 10fps, MPEG-4) [1.56 GB/day]
 - 24/7 audio stream (24kHz mp3) [.57 GB/day]
 - 24/7 1 photo per minute or other data [.57 GB/day]
 - 16/7 One 3MB data file per hour [72MB/day]

- ❑ A year of data: **990MB**
- ❑ 2007: Terabyte of data <\$300

Sensors in the (not-so-distant) future

□ Example:

- Video/photos from miniature pocket/cap camera
- Continuous audio recording, keyword detection
- Real-time HR data
- Real-time motion data all limbs, hip
- Real-time indoor/outdoor position
- Real-time position relative to other people
- Real-time data from home: objects touched/used
- Data on use of communication devices
- No encumbering or nerdy-looking devices
- Context-sensitive self report

Data analysis in the (not-so-distant) future

- ❑ Computers pre-process data:
 - Translate noisy sensor data into meaningful labels
E.G. Cooking, socializing, running, smoking, ...
- ❑ Computer helps researcher search data:
 - “find all the moments when the subject might have been cooking”
 - “query the subject whenever the subject is near another subject”
 - “show me video clips of moments when the subject was with other people”
 - “indicate where the subject spent the most time”

Personalized mobile computing device



Take your pick...

Powerful, inexpensive, sensor-enabled
mobile computing device *carried nearly everywhere*

The mobile computing device...

- ❑ Color touch screen
- ❑ Light, comfortable to carry everywhere
- ❑ 1GB+ disk space
- ❑ Sound player (MP3 and other)
- ❑ Sound recorder
- ❑ Camera
- ❑ Fingerprint recognizer
- ❑ 400+ MHz processor
- ❑ Always on wireless connection
- ❑ Battery life
- ❑ Cost (not for long)
- ❑ Barcode scanner
- ❑ Handwritten input
- ❑ Speech input
- ❑ Video game player
- ❑ GPS / location detection
- ❑ Accelerometers
- ❑ Biomonitors

New developments in pattern recognition

❑ Innovation:

- Real-time recognition of activities
(e.g. walking, running, posture, cooking ...)
- Recognition of affect
(e.g. frustration, stress, anger)
- Speech recognition
- Recognition of socialization activity

❑ Remaining challenges:

- Real-time recognition of many activities
- Unencumbering recognition of many emotional states

Technologist's interest

- ❑ Want to design technology for real-world environments and to test technology in context, but...
- ❑ Vast majority of homes and workplaces do not look anything like our labs and prototype environments!



Motivation for sensing/measurement tools

- ❑ Behavior is “situated”, i.e. influenced by environment
- ❑ Simulating natural setting in lab difficult (impossible?)
- ❑ Real environments are terribly complex
- ❑ Need sensors to measure *reaction to interventions* in context of everyday life

Examples

- New developments
- **Examples**
- Emerging opportunities
- Challenges

House_n: tools to study natural settings

Portable data
collection and intervention
toolkit



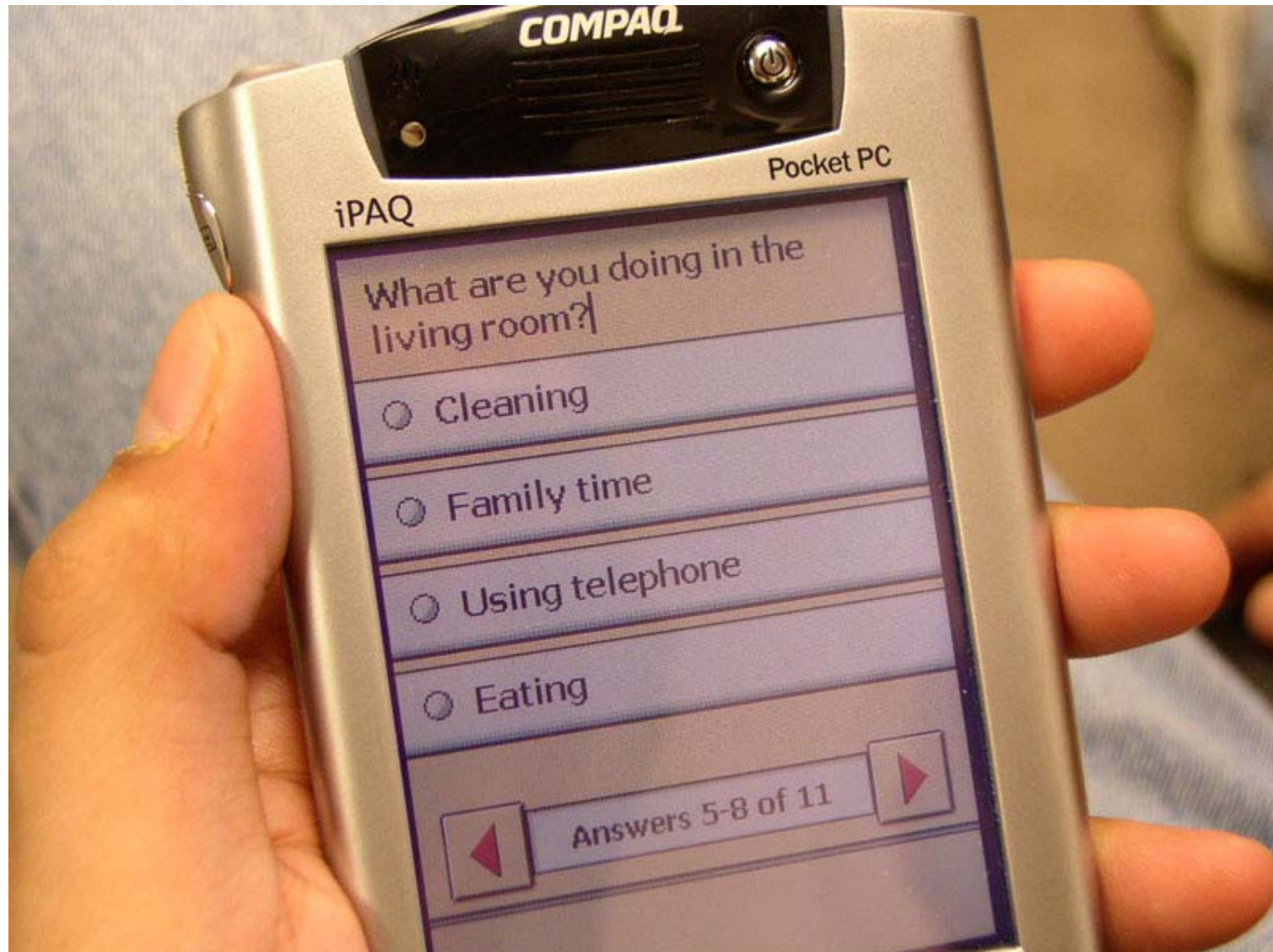
PlaceLab
residential research
facility





Context-aware experience sampling

Electronic experience sampling



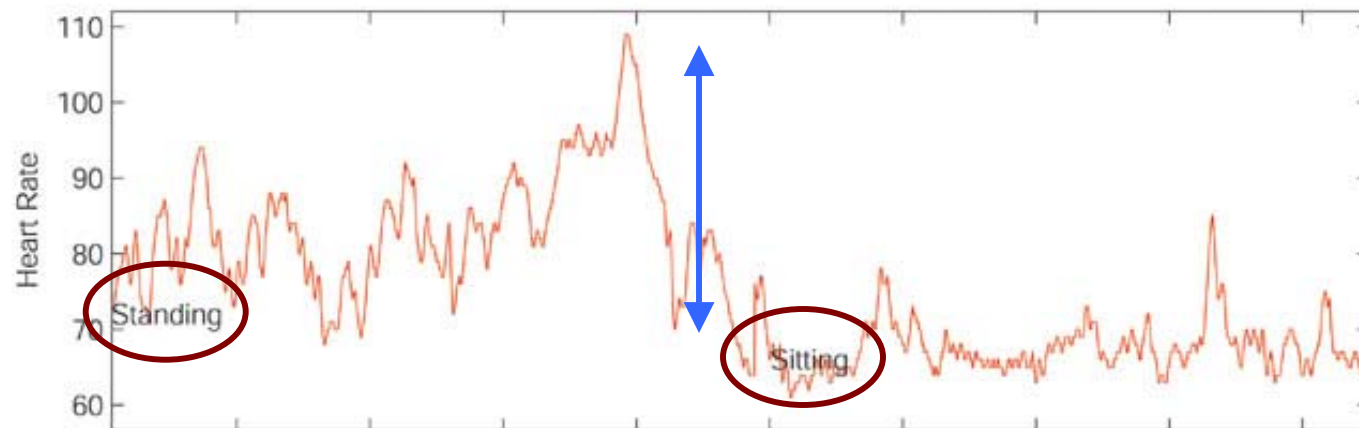
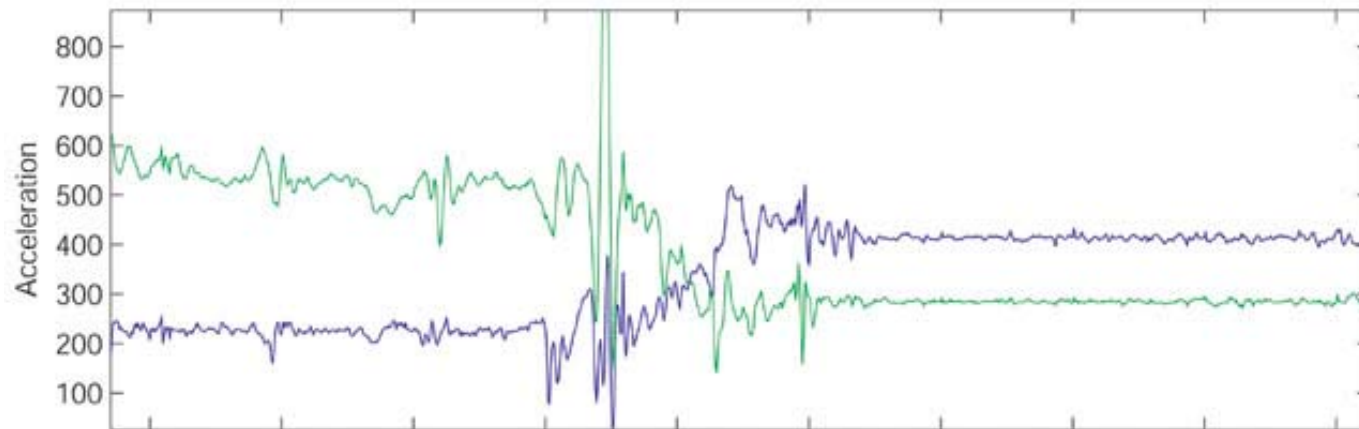
MIT version: new data collection capabilities



E.g.: trigger sample based on position



E.g.: trigger sample based on HR



Context-aware experience sampling

- ❑ Scheduling options
 - Fixed
 - Random within intervals
 - User-initiated
 - *Triggered by context*
- ❑ PDA plug-in sensors and sampling devices
 - GPS
 - Heart rate
 - Bar code scanner
 - Camera
 - Accelerometers

 - Future: Bluetooth

Context-aware experience sampling tool

- ❑ Uses at MIT:
 - Machine learning algorithm development
 - Physical activity interventions
 - Studying interruptions (using biometric data)
 - Planned: workplace studies
- ❑ Available to researchers
<http://caes.sourceforge.net>

The screenshot shows a mobile application interface for the Context-Aware Experience Sampling (CAES) tool. At the top, a yellow header bar contains the question "What were you doing at the beep?". Below this, there is a list of four activities, each preceded by an unchecked checkbox: "Preparing lunch", "Watching TV", "Getting ready for work", and "Sleeping". Each activity is on a separate line with a thin yellow border. Below the list, a yellow bar contains a navigation control with a left arrow, the text "Answers 1-4 of 12", and a right arrow. At the bottom, there are two icons: a speech bubble and a camera, both within yellow-bordered boxes.



Mobile activity recognition

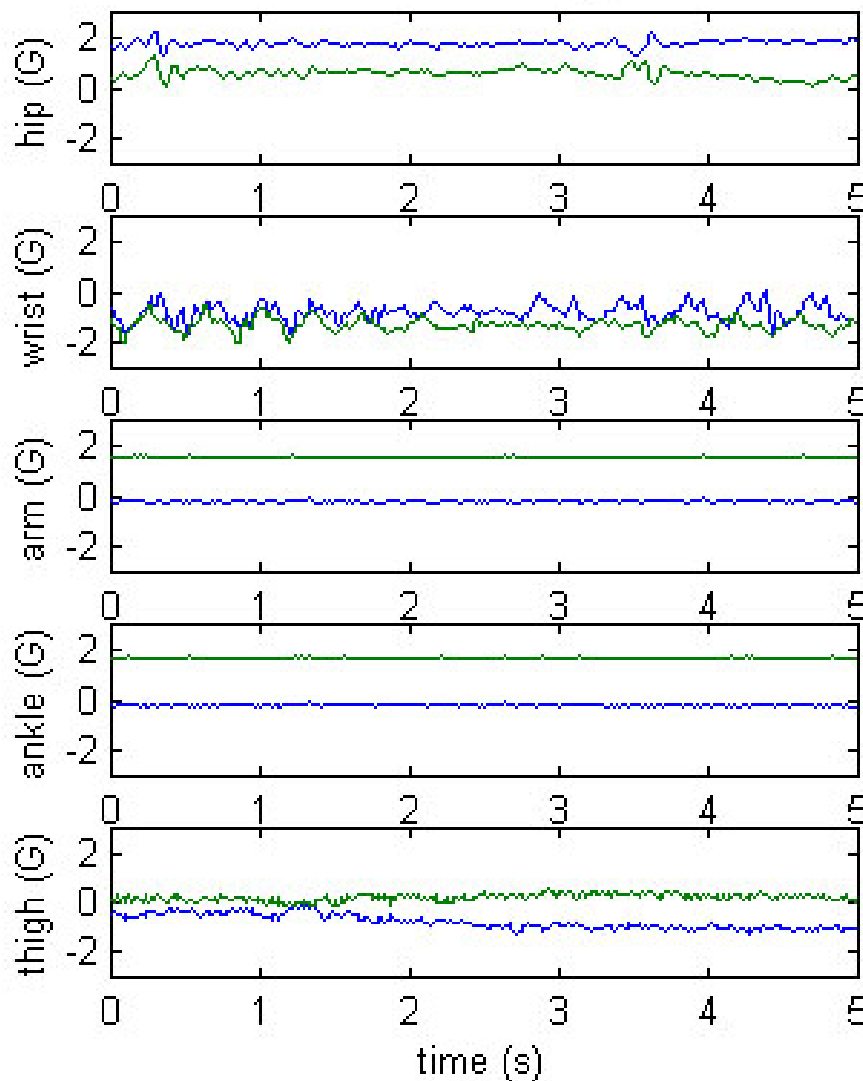
Multiple, wire-free accelerometers

- ❑ Placement
5 points
- ❑ Collect data up to 24 hours
- ❑ 2 axis, 85Hz sampling
- ❑ No wires
- ❑ Next version (Fall):
watch size, comfortable,
real-time wireless

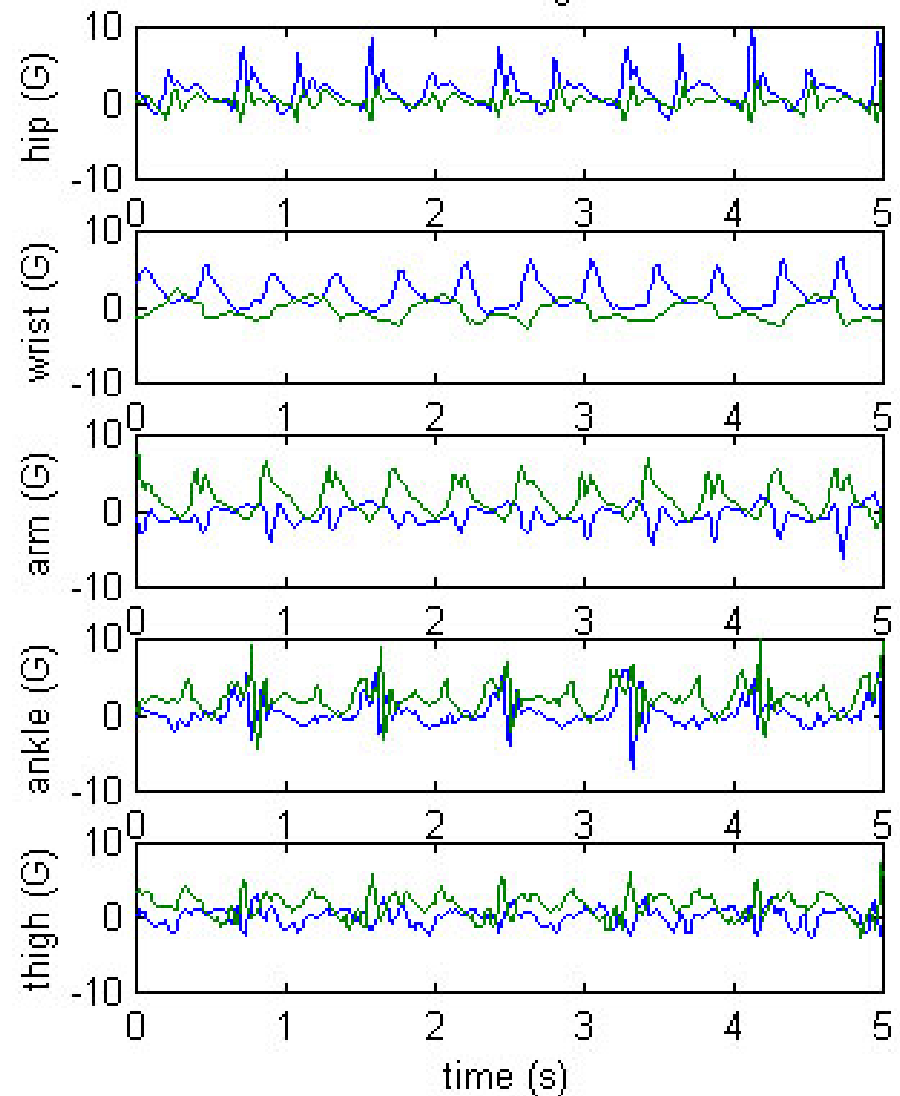


Mobile activity recognition

Tooth Brushing



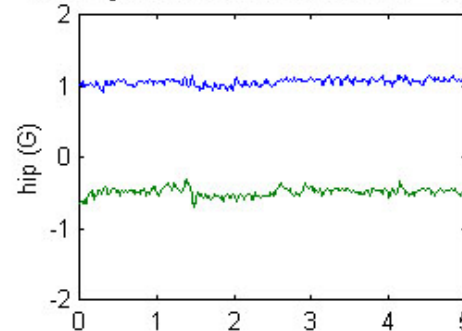
Running



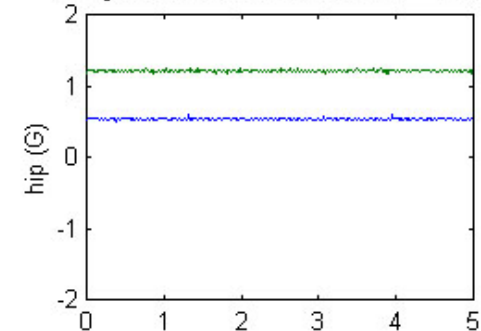
Mobile activity recognition

□ Features

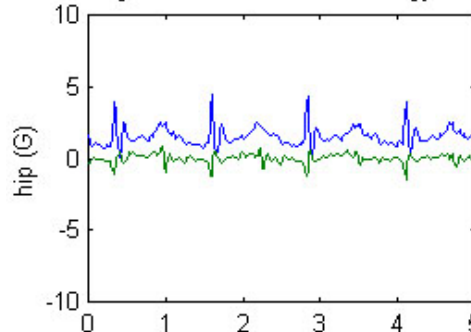
standing: mean vertical acceleration = 1.05 G



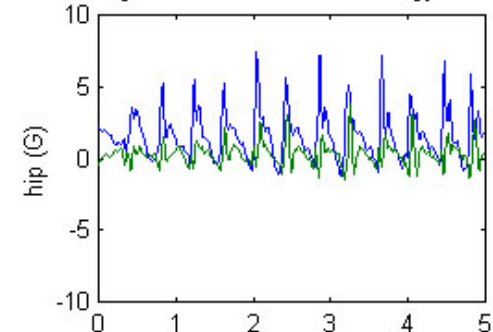
sitting: mean vertical acceleration = 0.54 G



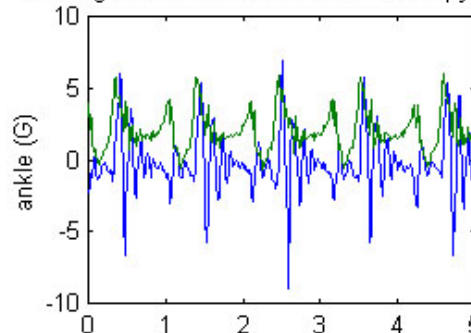
walking: vertical acceleration energy = 68.4



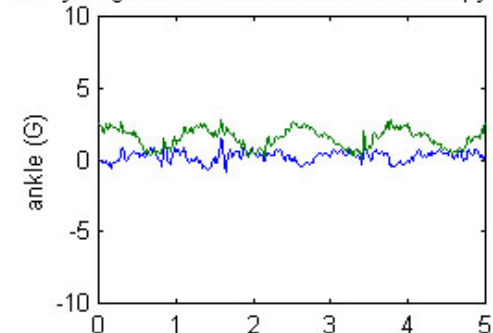
running: vertical acceleration energy = 685.2



walking: forward acceleration FFT entropy = 0.7



bicycling: forward acceleration FFT entropy = 0.9



Mobile activity recognition

- Aggregate confusion matrix for fast C4.5 classifier based on leave-one-subject out validation for 20 subjects using laboratory and obstacle course data.

a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t		--- classified as
942	46	0	0	2	0	0	0	8	3	8	1	4	2	7	0	3	8	8	8		a = walking
23	1183	9	0	3	2	0	0	8	1	3	8	14	1	16	0	8	53	38	11		b = walking while carrying item
0	9	762	11	0	1	17	3	0	0	0	0	0	0	0	1	0	0	0	0		c = sitting and relaxing
0	0	10	893	1	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0		d = working on computer
0	0	0	7	774	11	0	0	0	6	1	2	2	0	4	0	2	0	0	0		e = standing still
0	2	1	8	12	712	9	1	0	0	2	1	10	1	18	0	26	1	4	3		f = eating or drinking
0	0	43	21	9	1	320	28	0	0	0	0	0	0	0	0	0	0	0	1		g = watching TV
0	0	23	1	1	6	16	961	9	0	2	0	0	1	0	1	2	0	2	22		h = reading
14	12	0	0	1	1	0	17	491	10	1	1	1	1	1	0	1	3	4	1		i = running
0	1	0	0	5	0	0	0	8	830	10	0	1	0	3	0	2	1	0	1		j = bicycling
9	3	2	16	30	22	45	9	2	35	309	37	26	21	99	1	38	12	3	26		k = stretching
4	10	0	0	6	5	2	7	0	6	23	500	13	2	9	3	6	5	3	2		l = strength-training
1	7	0	0	5	10	0	0	0	0	2	9	403	11	10	1	26	1	6	4		m = scrubbing
1	0	0	0	0	3	1	0	0	2	0	1	9	885	11	0	1	0	2	2		n = vacuuming
1	1	0	0	1	6	0	0	0	1	4	1	4	7	822	8	4	0	1	3		o = folding laundry
0	0	4	9	0	2	1	7	0	0	0	0	1	8	10	791	8	0	0	0		p = lying down and relaxing
1	2	0	0	3	32	0	0	0	1	5	0	18	7	10	9	637	10	2	10		q = brushing teeth
7	14	0	0	1	1	0	0	0	3	2	1	1	0	2	0	12	351	10	5		r = climbing stairs
84	70	0	7	20	60	0	0	8	40	33	11	24	34	40	0	0	59	502	100		s = riding elevator
5	2	0	0	5	6	0	1	0	1	0	3	3	1	0	0	3	7	16	127		t = riding escalator

Current work

- ❑ Development of comfortable, 24 hour wireless, 2-3 axis mobile accelerometers
 - Smaller than CSA actigraph
 - Real-time data streaming
 - High sampling rate

- ❑ Real-time mobile activity recognition for context-sensitive data collection

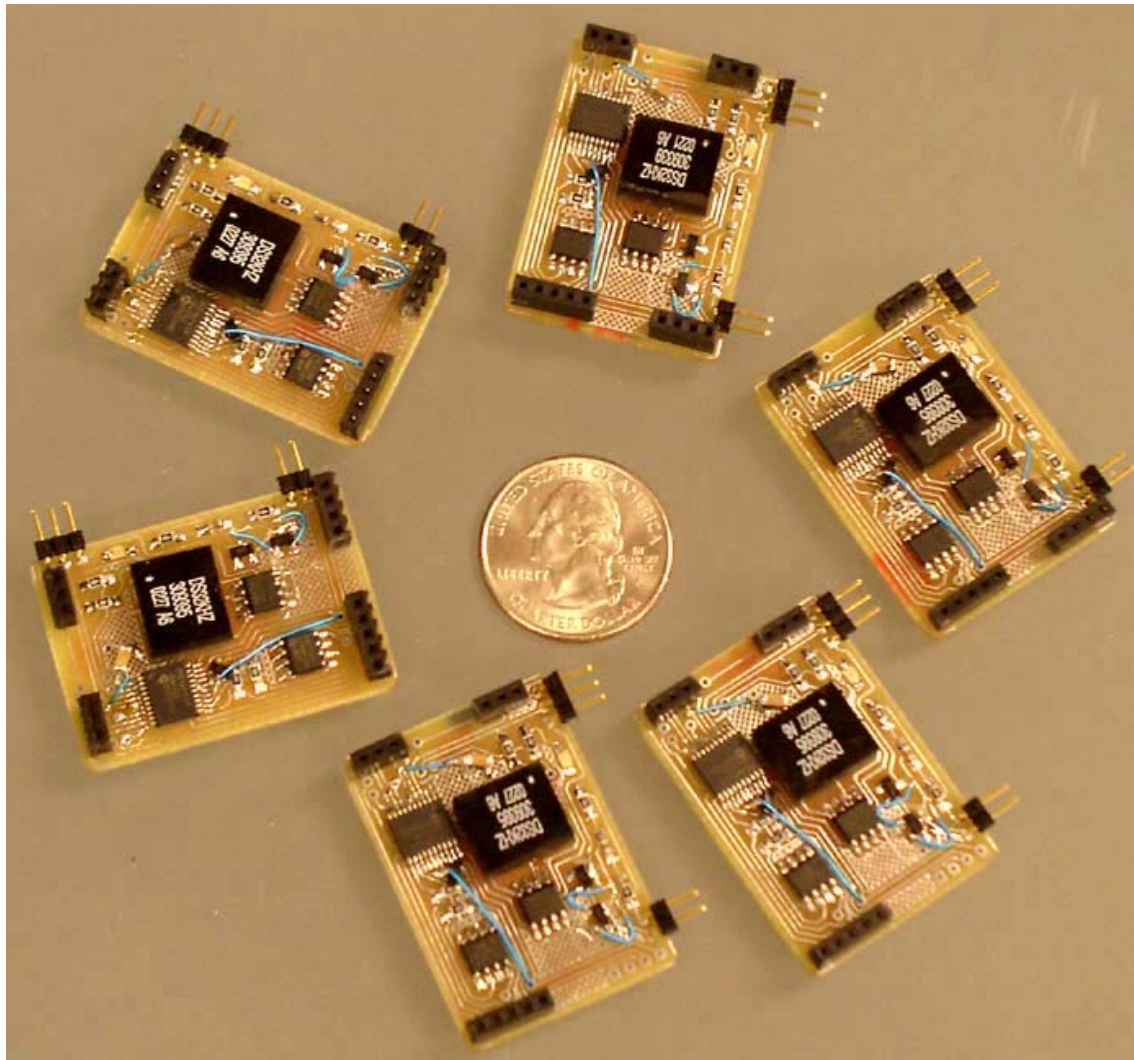


Tape-on environmental sensors

Environmental sensor kit

- ❑ Data collection board with swappable sensor
 - ❑ Small, robust
 - ❑ Relatively inexpensive (\$27 each at qty of 150)
 - ❑ Collect state change data 4+ weeks
 - ❑ +/- 2 second timestamp synchronization
 - ❑ Tape-on install
-
- ❑ Non stigmatizing
 - ❑ Relatively non-invasive

Environmental sensor kit



One subject's home



- ❑ 3 hours with small team
- ❑ Install: tape-on
- ❑ Approx. 85-100 sensors in small 1 bedroom
- ❑ On | Off
- ❑ Open | Closed
- ❑ Position | Identity

Studying behavior in context













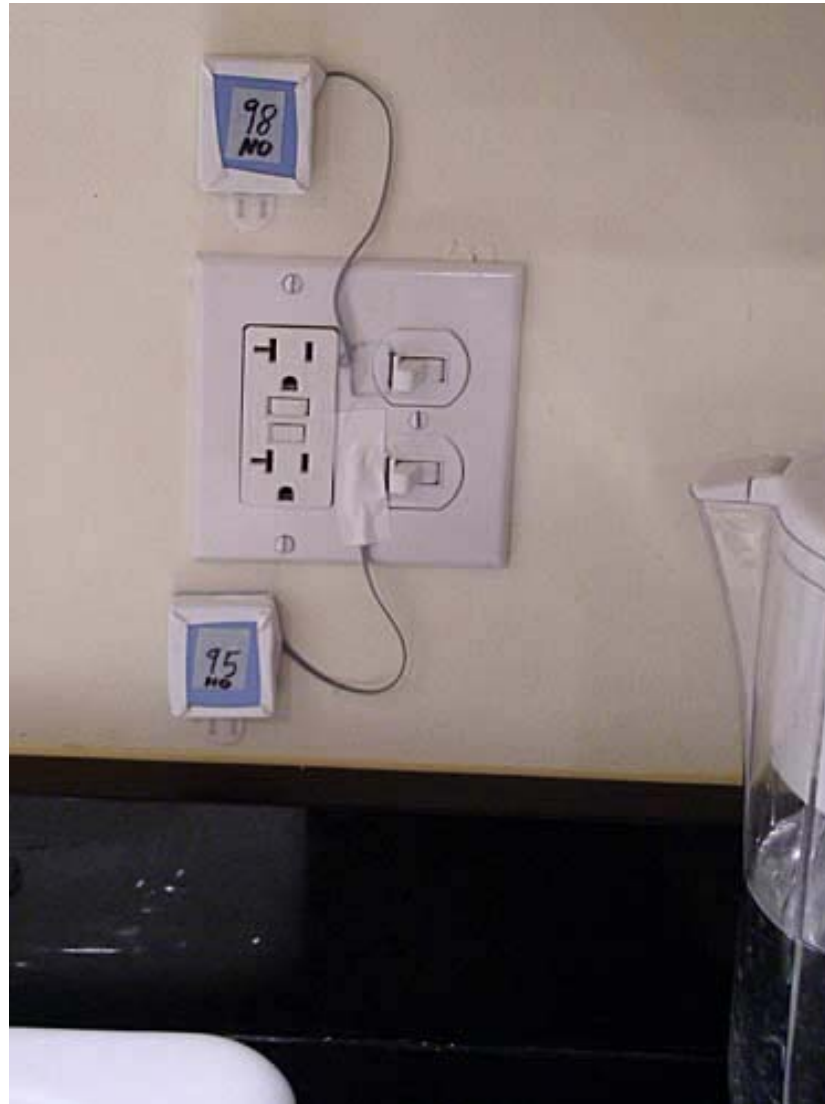
















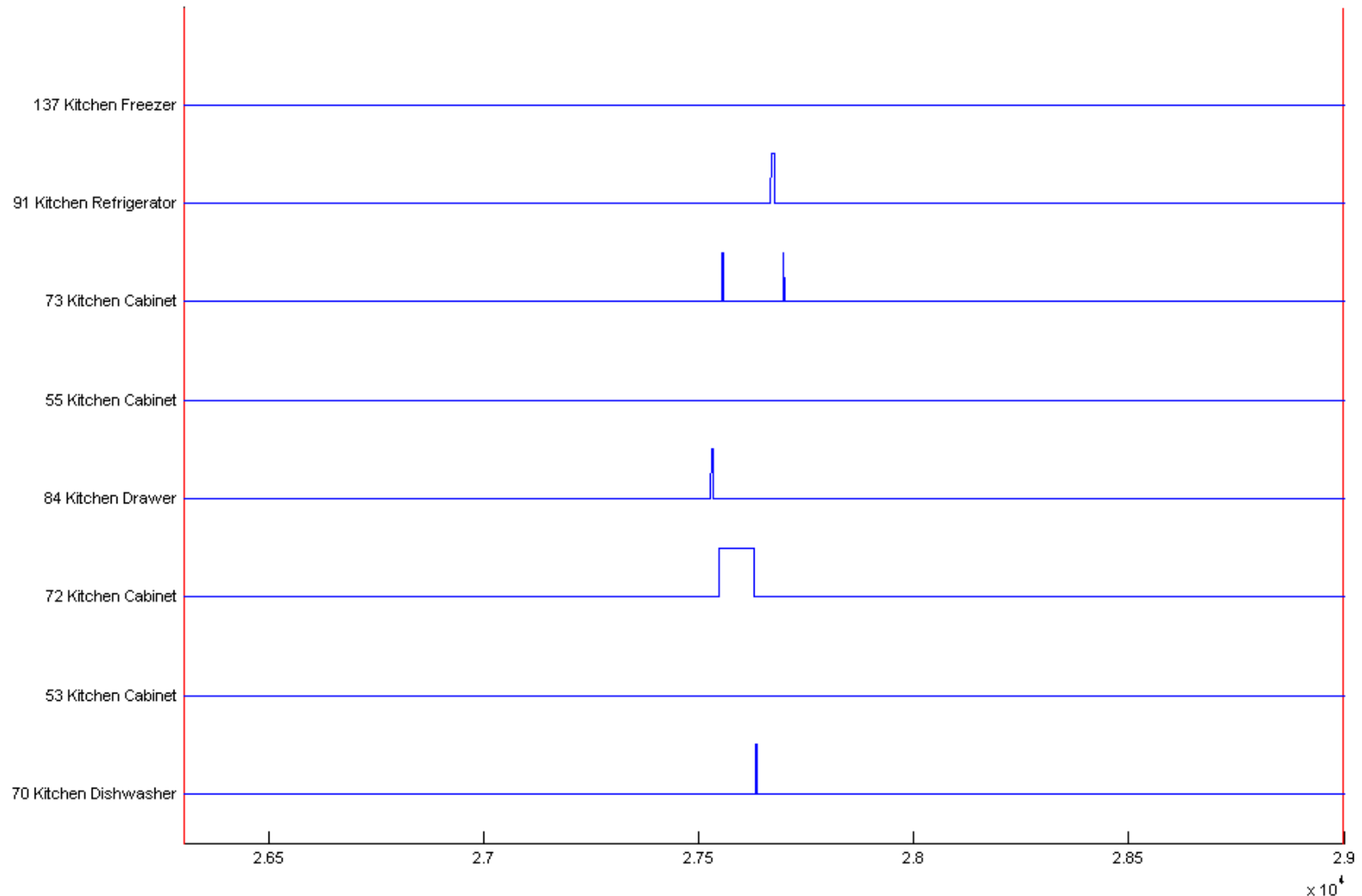






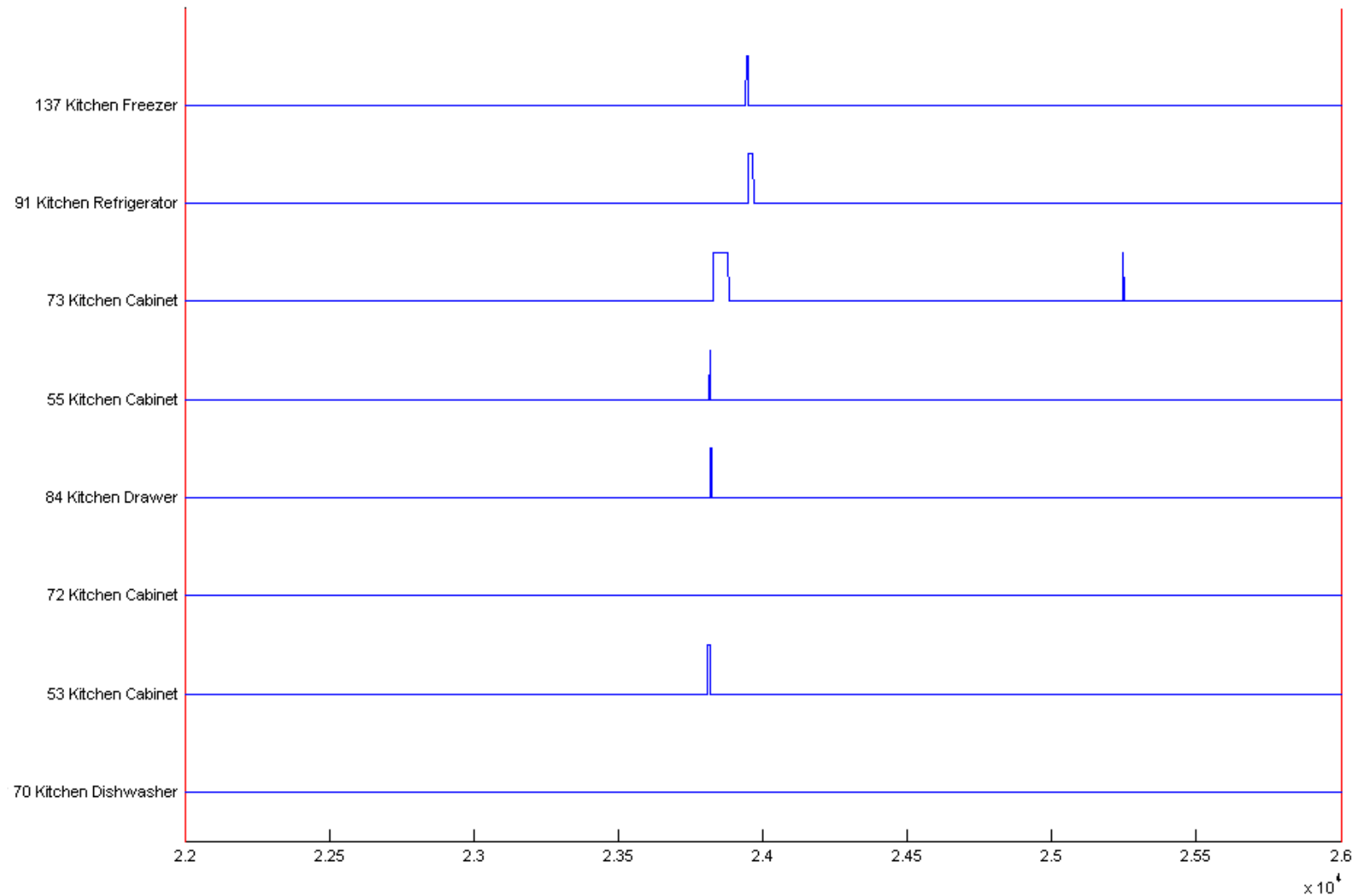
Cooking breakfast 3/27

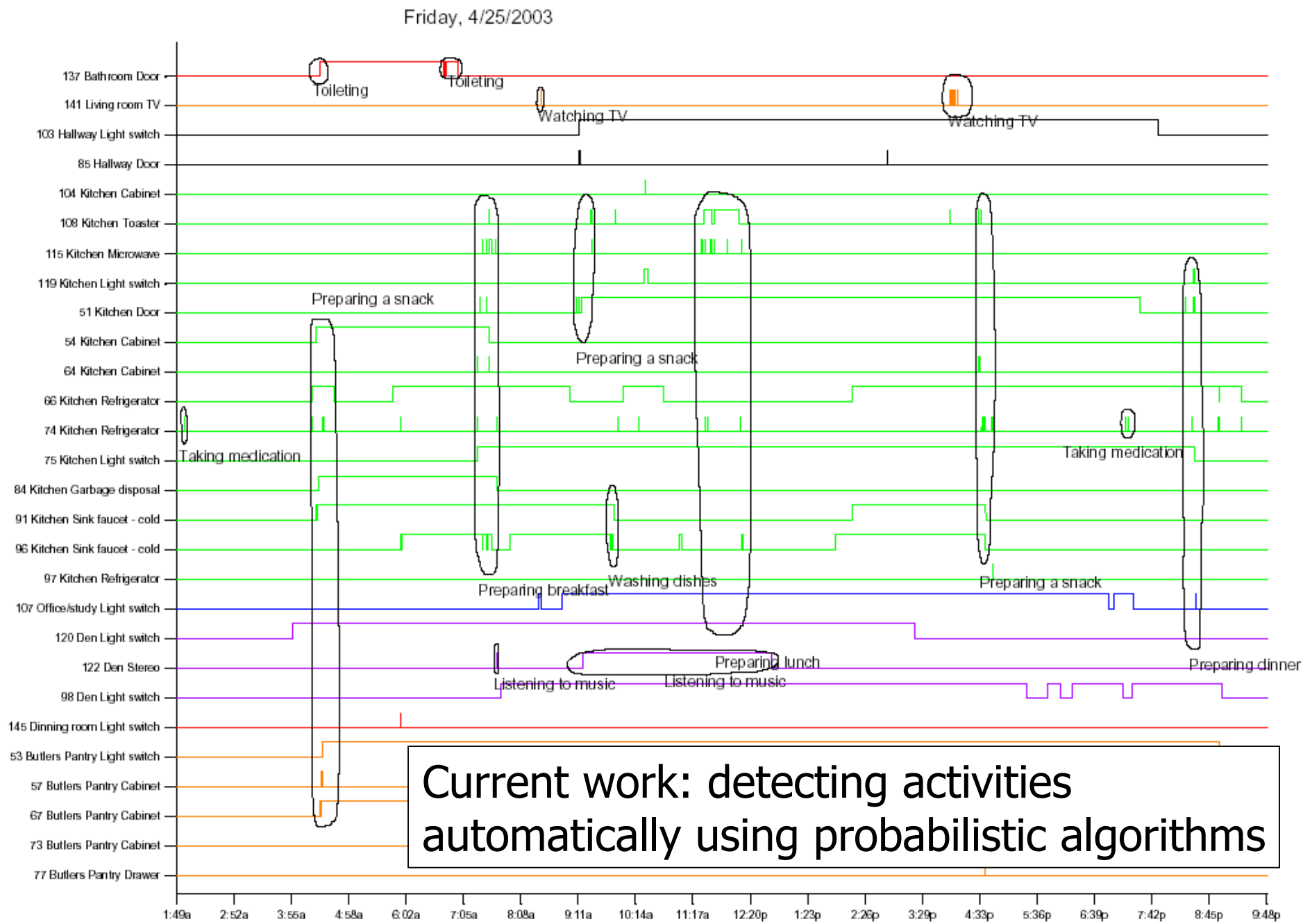
Thursday, 3/27/2003



Cooking breakfast 4/01

Tuesday, 4/1/2003

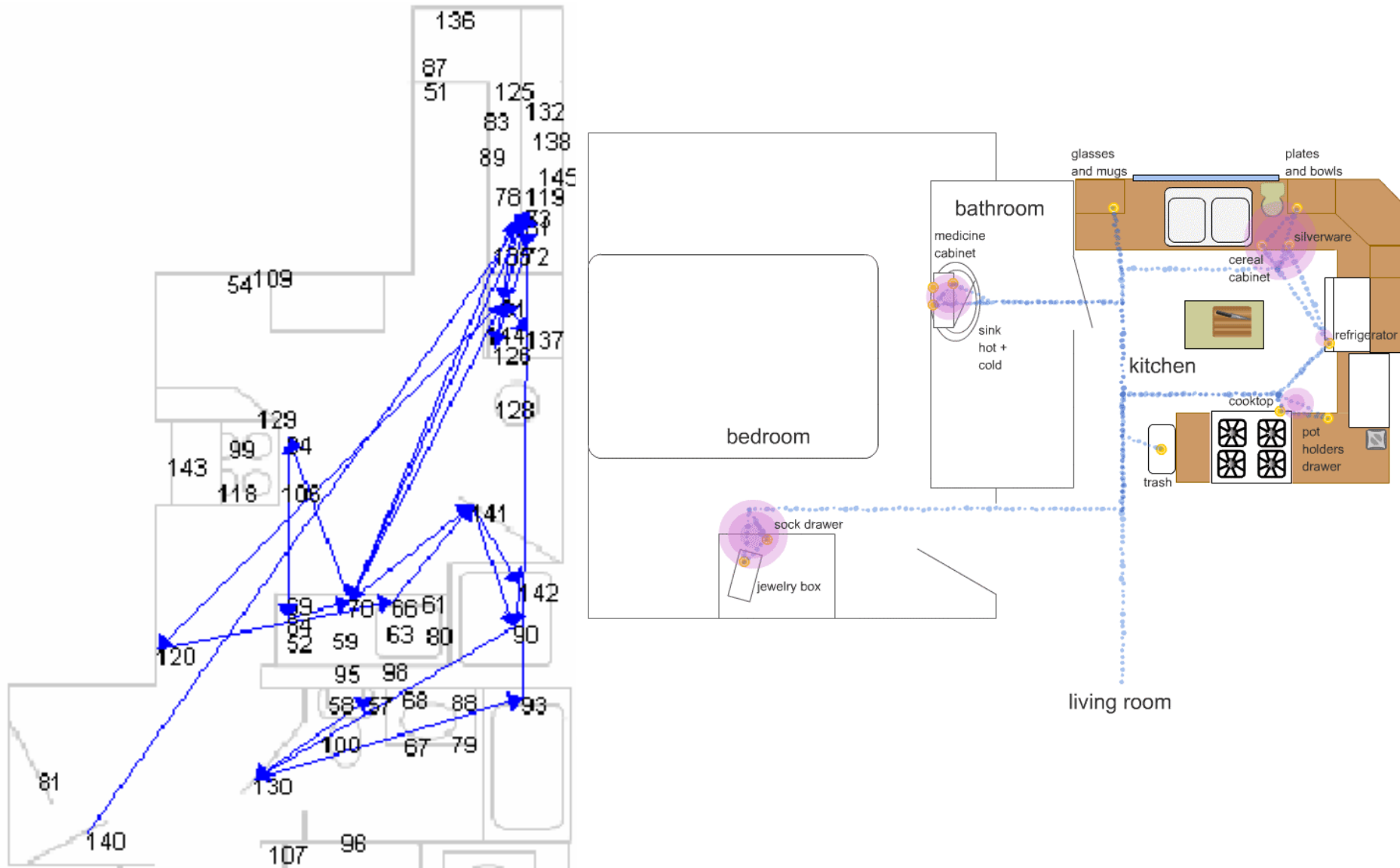








Collaborative development of interventions





The PlaceLab

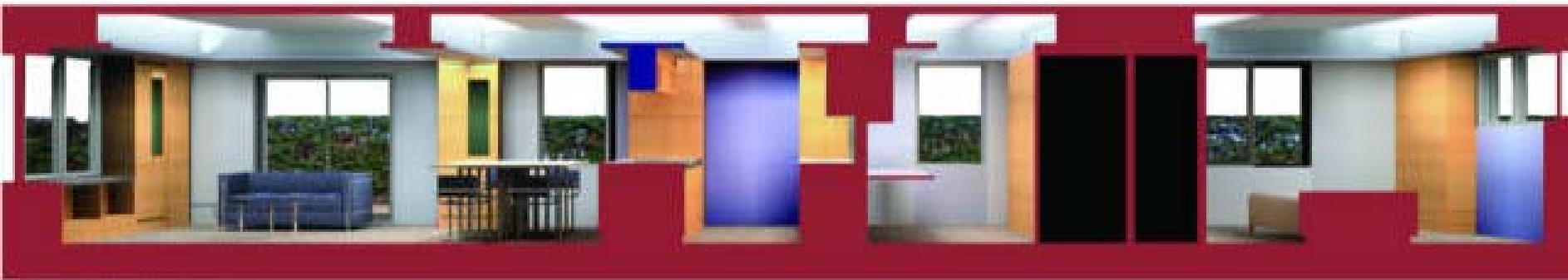
- A residential laboratory for studying behavior in the home

PlaceLab

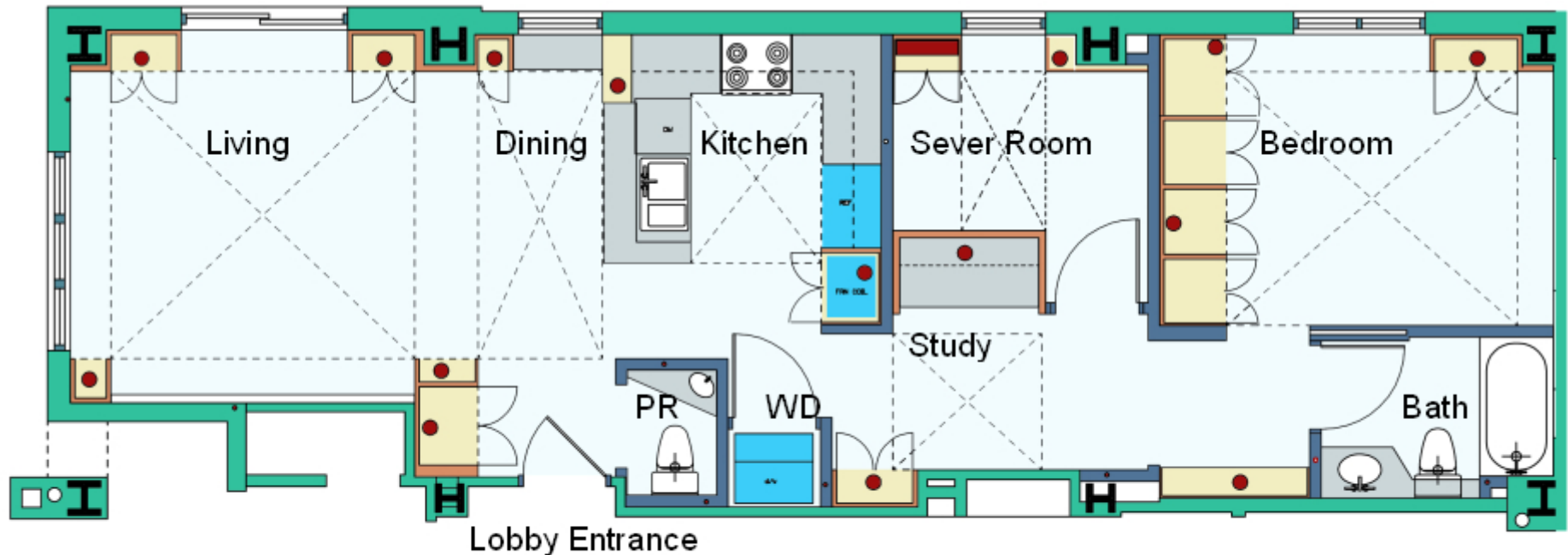


- ❑ **Not** a prototype
- ❑ **Not** a demonstration

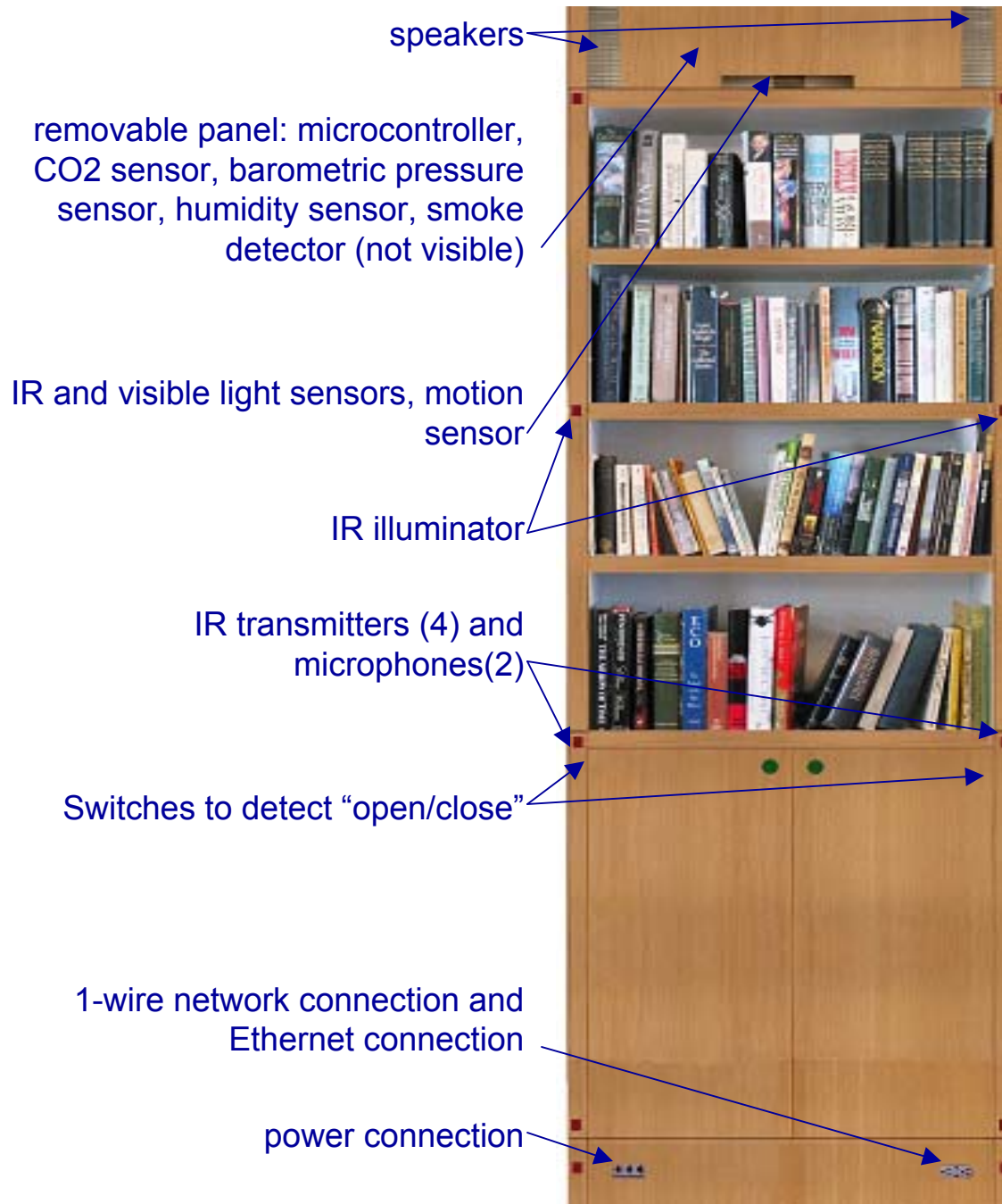
PlaceLab floor plan / cabinetry



Section Perspective

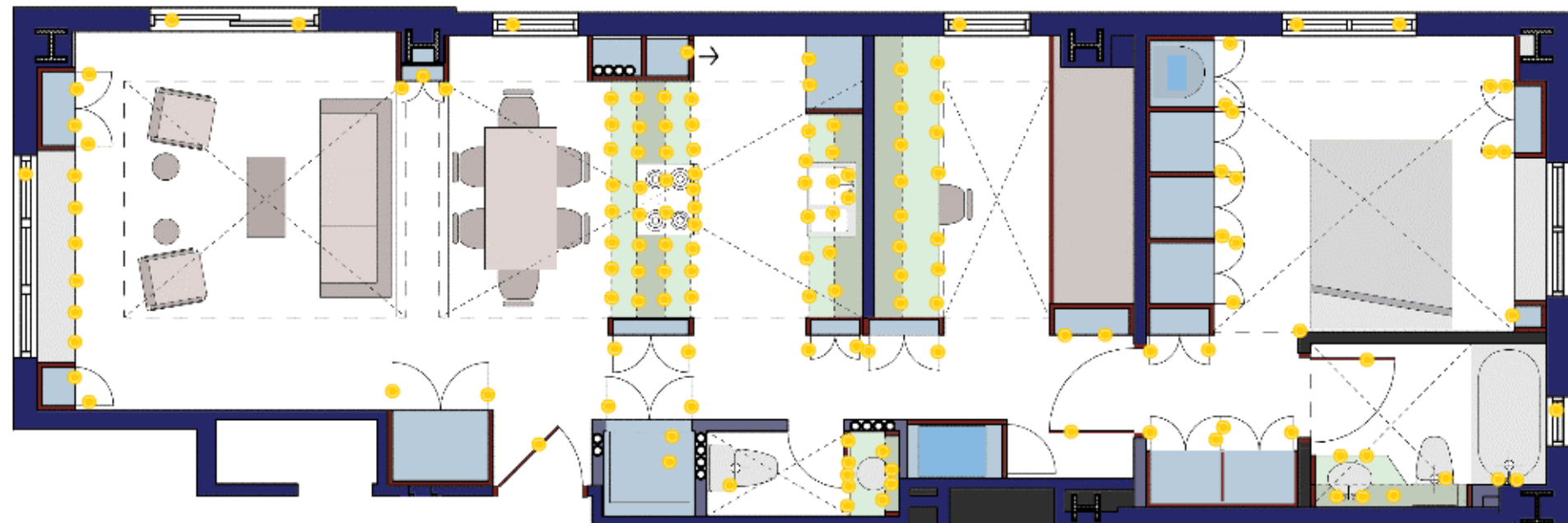


Floor Plan



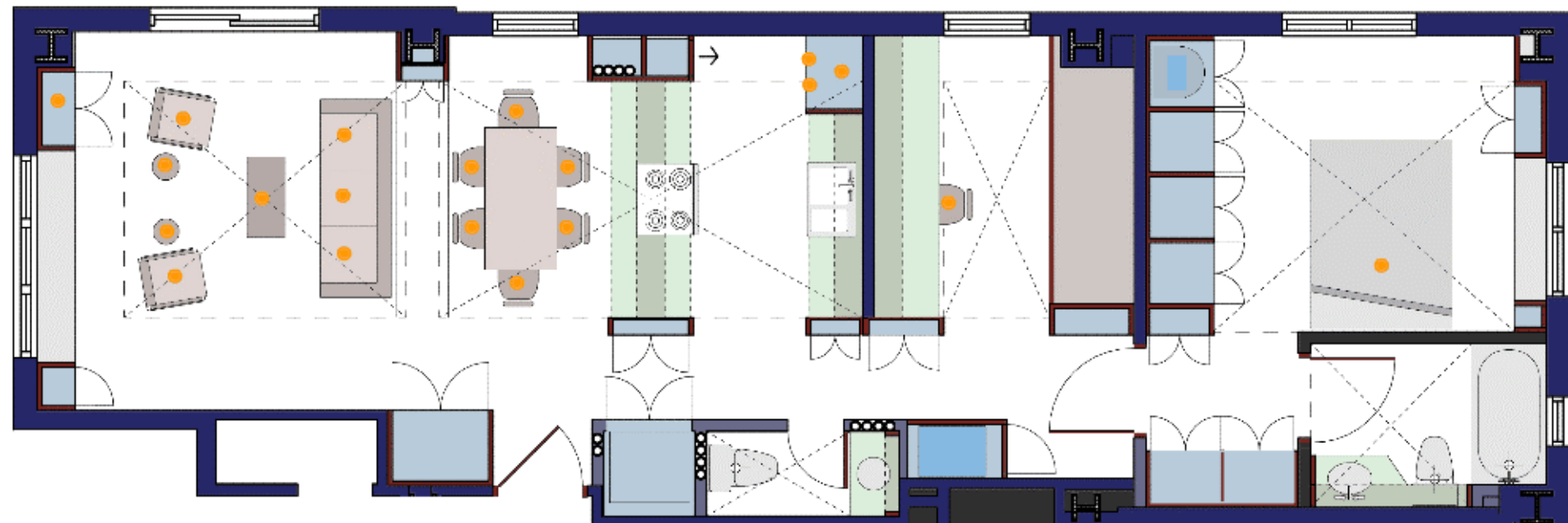
Each infill cabinet

State of fixed things



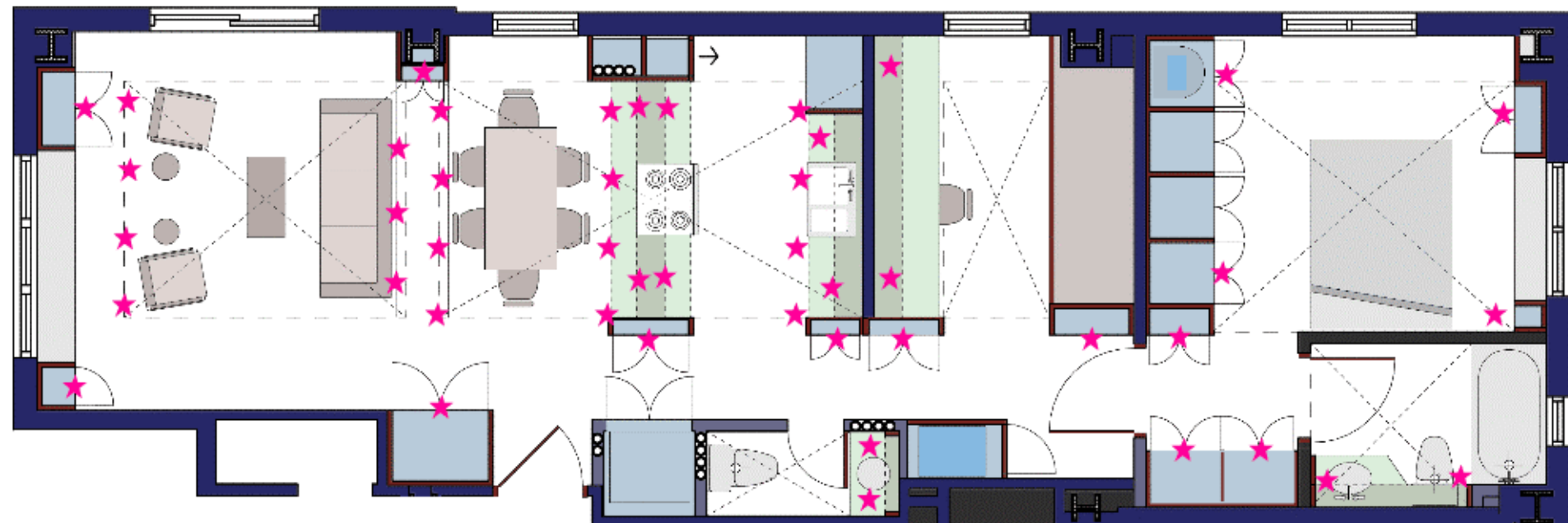
Switch sensors in cabinets and appliances

State of movable things



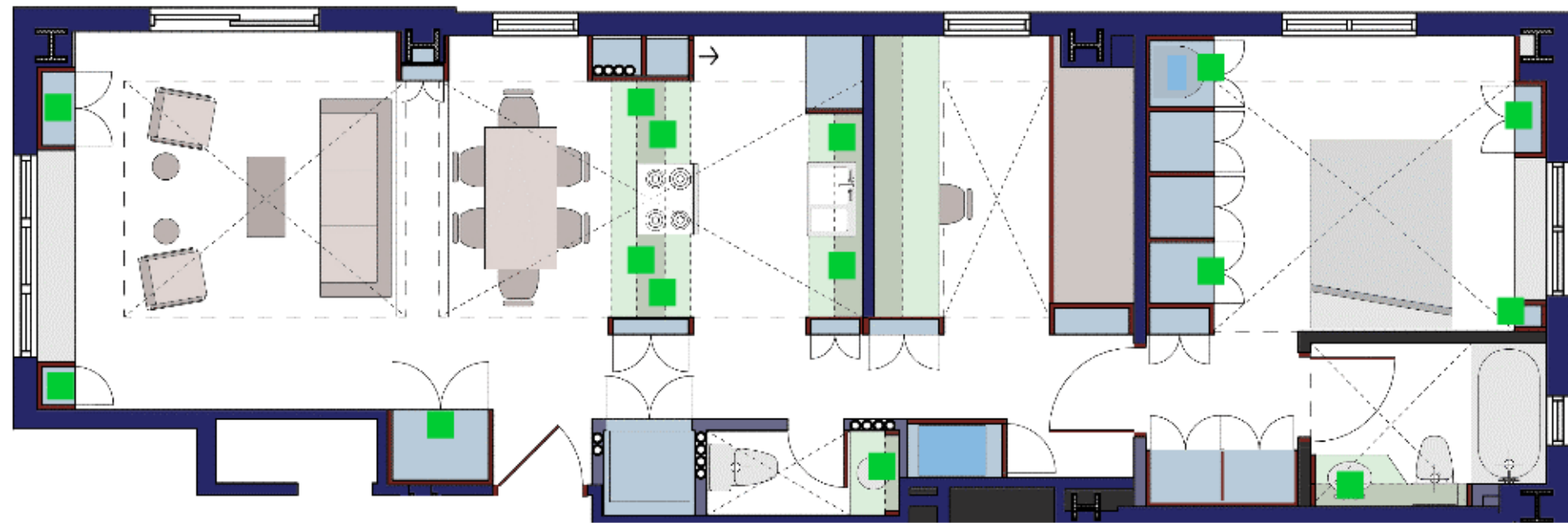
Wireless sensors in movable furniture

Location/identity of people



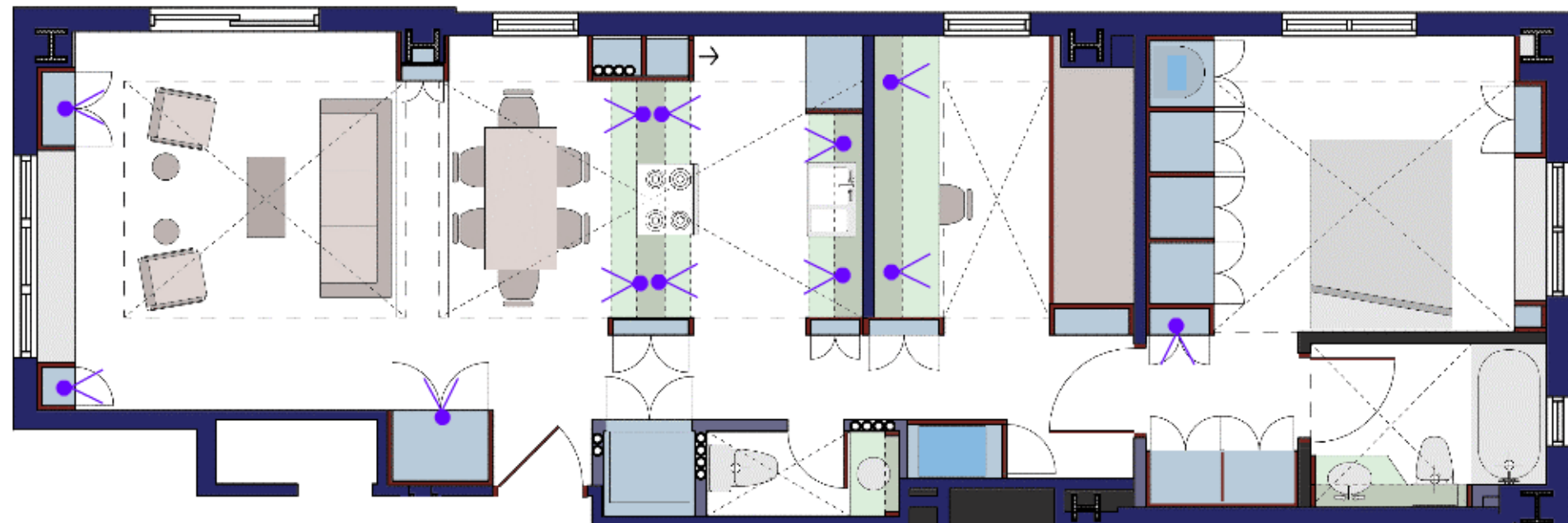
IR transmitters

Environmental conditions



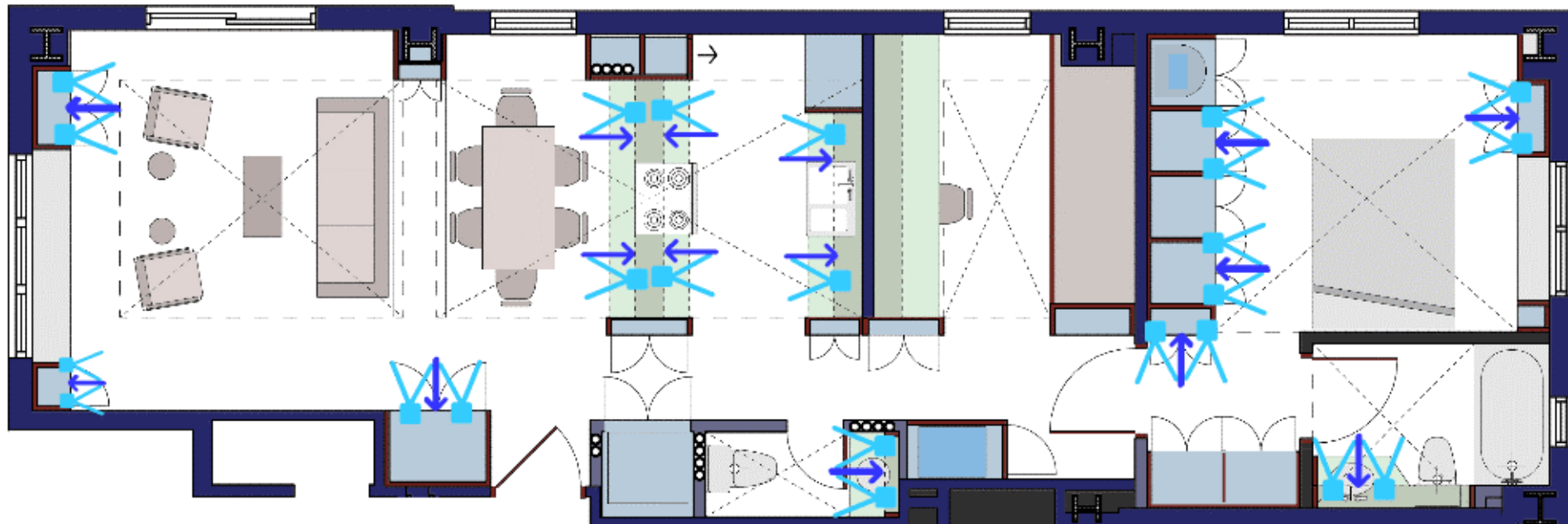
Locations of temperature, humidity, CO, CO2, and smoke sensors

Optical sensors (IR & visible)



IR and visible light sensors

Communication w/ directed audio



Speakers and microphones

PlaceLab: Design for real people

- ❑ Heard yesterday: “We are assuming our research subjects are behaving like rats”
- ❑ Use measurement tools to study:
 - How to study people in natural settings
 - How to show user’s own data to get them to help researchers design new, effective interventions

Emerging opportunities

- New developments
- Examples
- **Emerging opportunities**
- Challenges

Measuring and motivating health behavior

❑ Switch/bend sensors

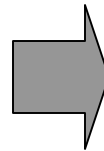
- Doors
- Cabinets
- Drawers
- Thresholds
- Appliances
- Objects

❑ Wearable sensors

- Accelerometers
- Heart rate monitor
- Self report

❑ Multi-purpose sensors

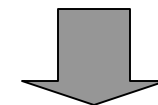
- People-locator tags
- Auditory sensors
- Optical sensors



new
machine
learning
algorithms

❑ Activity recognition

- ❑ Eating meals
- ❑ Talking
- ❑ Sleeping patterns
- ❑ Taking medications
- ❑ Cleaning
- ❑ Cooking
- ❑ ...

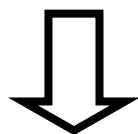


health
applications

Detect **change** in activity;
Motivate behavior changes;
Provide info at teachable moment

Best bet: link advice with activity

- ❑ Simple messages (points of decision/behavior/consequence)
- ❑ Right time ← Requires computational sensing
- ❑ Right place ← Requires “pixels where you are”
- ❑ Non-disruptive ← Requires attention to UI design



- ❑ Big impact
 - 20% shown for energy
 - Substantial gains for preventive medicine

Challenges

- New developments
- Examples
- Emerging opportunities
- **Challenges**

Volume of data / ethical collection

- ❑ Terrabytes possible
- ❑ Annotation can be time consuming, costly, and challenging
- ❑ Ethical issues may be raised by data collection

Data analysis techniques

- ❑ New types of multi-modal data
- ❑ Sensor algorithms noisy/probabilistic
- ❑ Desired contextual cues can be ill-defined:
 - E.g. "Cooking"
 - E.g. "Jittery"
 - E.g. "Getting dressed"
 - E.g. "Busy"

Thank you!

- ❑ For more information:
 - intille@mit.edu
 - http://architecture.mit.edu/house_n
 - ❑ Looking for preventive health collaborators
 - ❑ Portable tools available
 - ❑ PlaceLab opens in October.
Call for proposals soon.
- (Propose a study on EMA and interruption?)